

Do Occupants in a Building exhibit patterns in Energy Consumption? Analyzing Clusters in Energy Social Games

Hari Prasanna Das
Ph.D. Scholar
Department of EECS, UC Berkeley



Joint work with



Hari Prasanna Das
EECS, UC Berkeley



Ioannis C. Konstantakopoulos
EECS, UC Berkeley



Aummul B. Manasawala
IEOR, UC Berkeley



Tanya Veeravalli
EECS, UC Berkeley



Huihan Liu
EECS, UC Berkeley



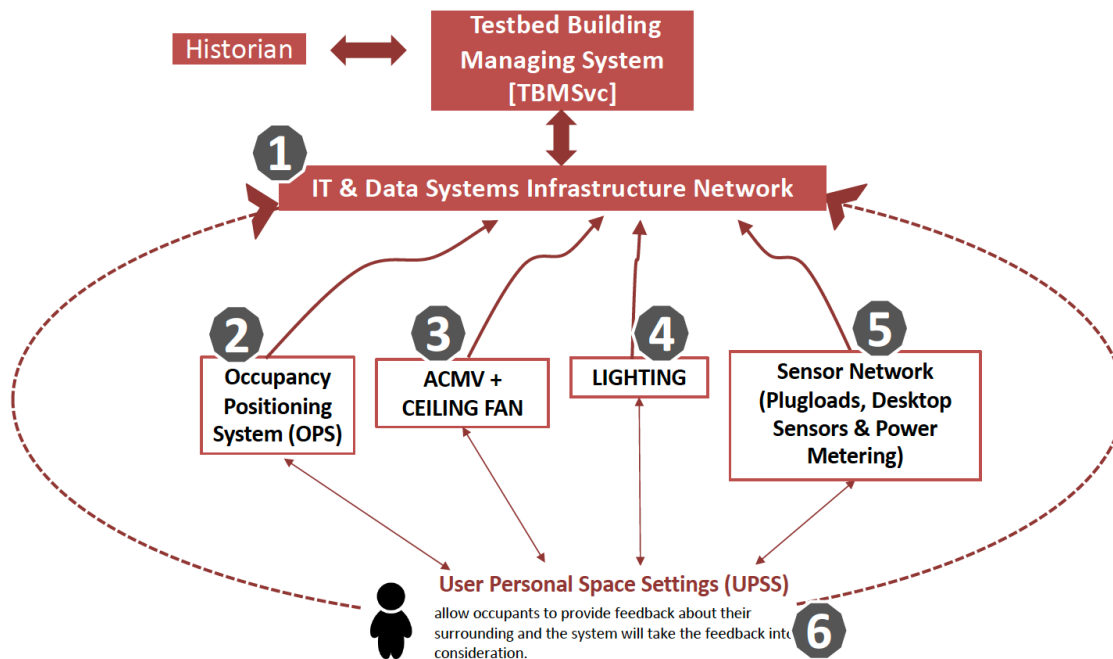
Costas J. Spanos
EECS, UC Berkeley

The Smart Building Paradigm

- Energy Consumption of buildings, both residential and commercial, account for approximately 40% of all energy usage in the U.S.
- Achieving energy efficiency in buildings is crucial
- Methods for achieving energy efficiency:

Making **building infrastructure** smart and energy efficient

Making **occupants** energy efficient



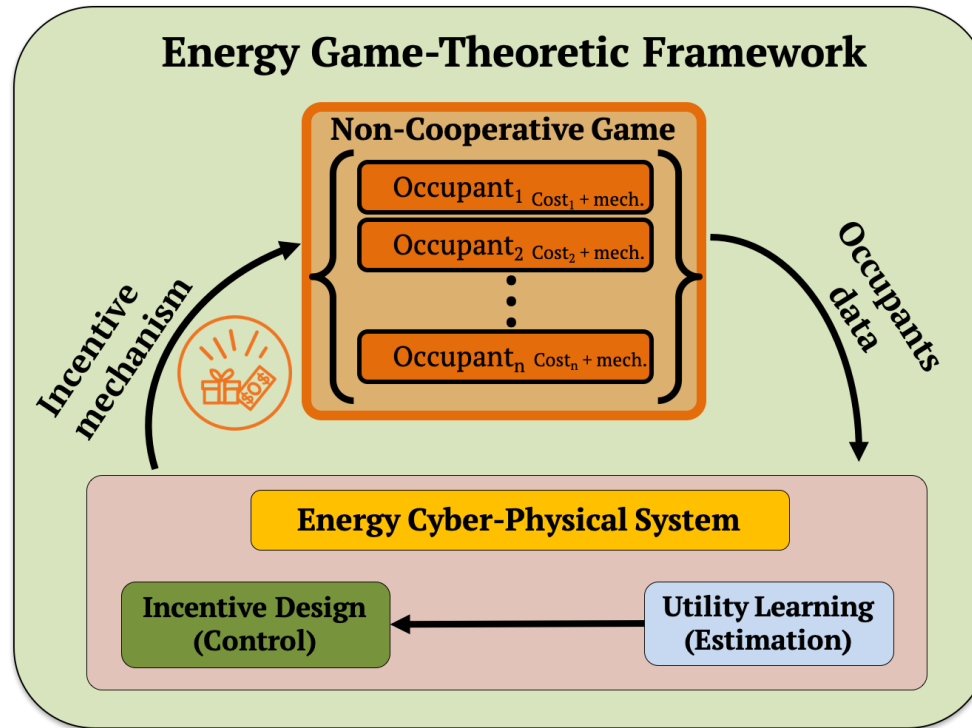
Energy Game-Theoretic Frameworks

Source: Singapore Berkeley Building Efficiency and Sustainability in the Tropics (SinBerBEST) www.sinberbest.berkeley.edu



Energy Game-Theoretic Framework

Incentivize occupants to modify their behavior in a competitive game setting so that the over-all energy consumption in the building is reduced.

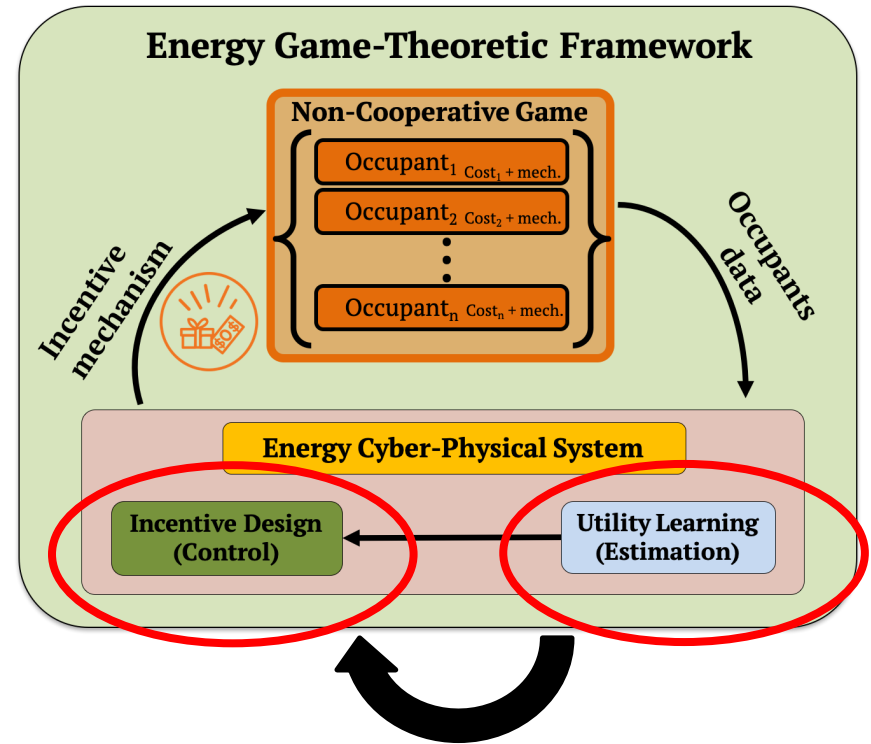


Utility learning is hard

To efficiently decide incentive for each occupant/player in the game, we need to know their utility function (preference towards energy usage)

Individual Utility learning is hard

- Number of players is high
- Quality data for each player unavailable
- Human behavior resulting in utility function has high variance

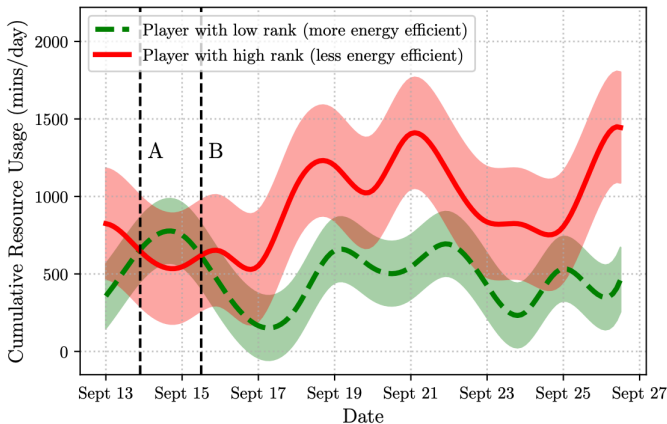


Our Proposal: Segment the energy usage behavior of players into finite clusters. Under the assumption that players in a cluster will behave synchronously.

Supervised vs. Unsupervised Segmentation

Supervised Segmentation

- Requires a supervision signal: we use rank of player
- Segments players as a whole into different classes **Undesirable**



- Provides labels of the classes as high/medium/low energy efficient **Desirable**

Unsupervised Segmentation

- No supervision required
- Segments energy usage behaviors into different clusters **Desirable**

- No information about labelling of clusters **Undesirable**

Our Approach: A hybrid segmentation method



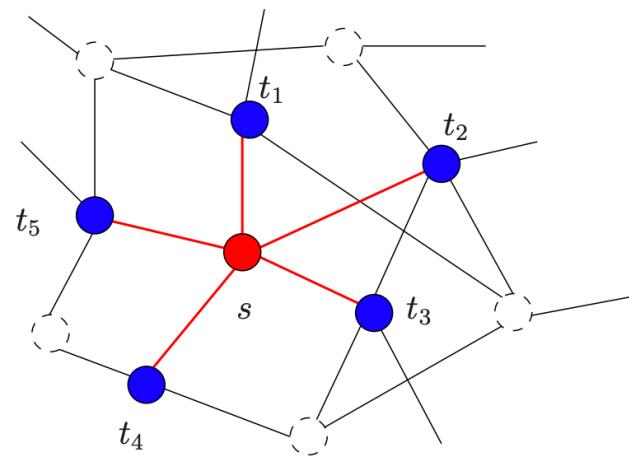
Tool for proposed segmentation: Graphical Lasso

- Graphical Lasso is a sparse penalized maximum likelihood estimator
- Features (Y) are associated with the vertex set $V = \{1, 2, \dots, S\}$ of some underlying graph.
- The structure of the graph is utilized to derive inferences about the relationship between the features.
- For undirected graphical models, node for Y_s is conditionally independent of nodes not directly connected to it given $Y_{V \setminus s}$. So the predictor for Y_s is written as,

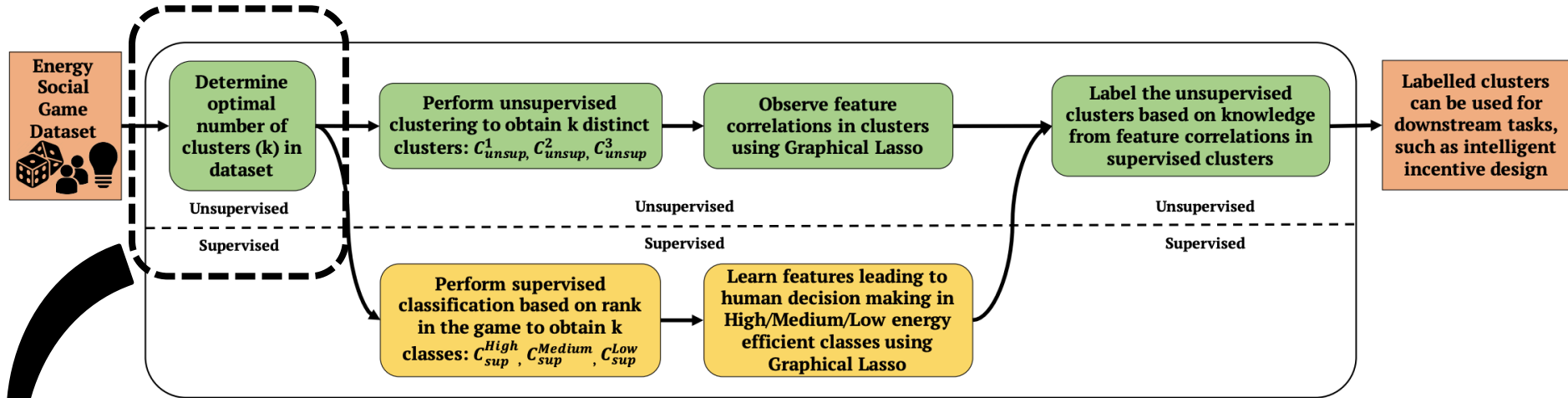
$$Y_s = Y_{V \setminus s}^T \cdot \beta^s + W_{V \setminus s}$$

- The β^s terms dictate the edge set for node s in the graph. Obtain β^s , by solving the lasso problem

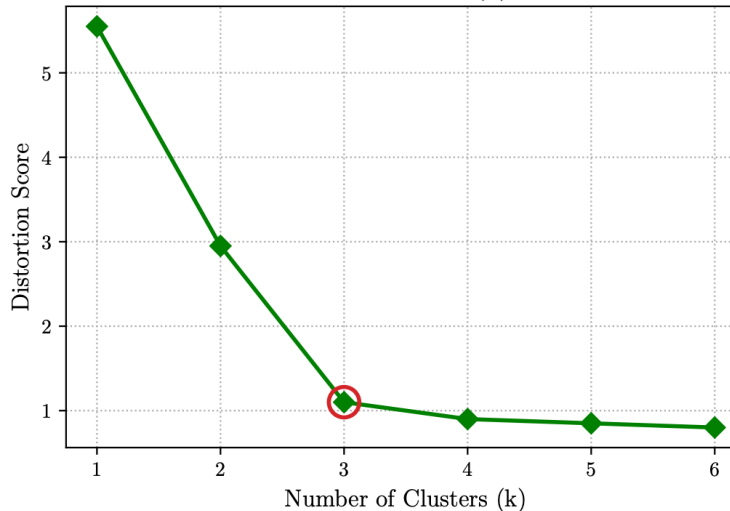
$$\hat{\beta}^s \in \operatorname{argmin}_{\beta^s \in \mathbb{R}^{S-1}} \left\{ \frac{1}{2N} \sum_{j=1}^N (y_{js} - y_{j,V \setminus s}^T \beta^s)^2 + \lambda \|\beta^s\|_1 \right\}$$



Proposed Segmentation Method



Distortion score vs number of clusters(k) for K-means clustering



Social Game Dataset

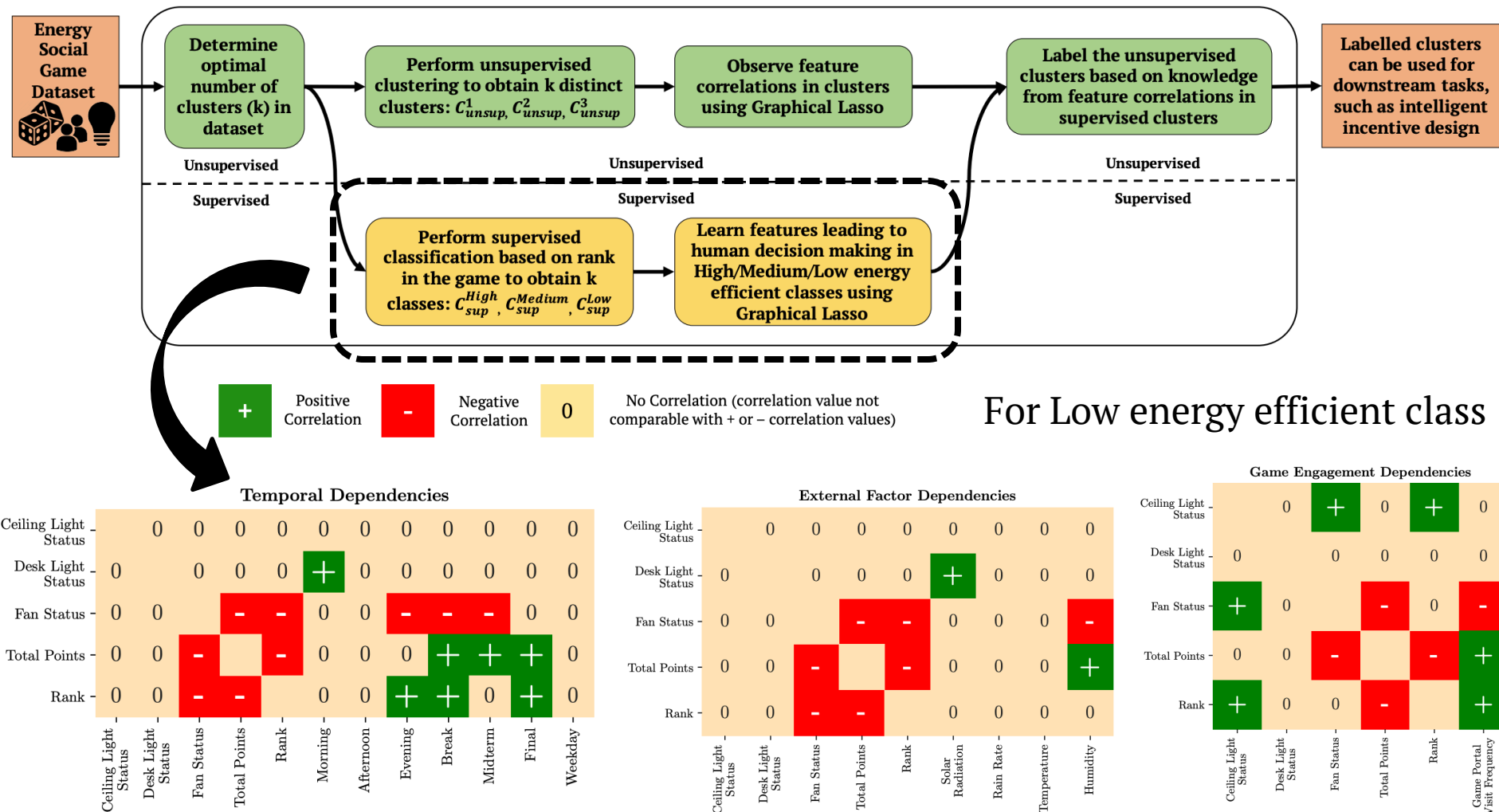
Energy Social Game time-stamped data in per-minute resolution:

1. Resource (Ceiling/Desk Light, Fan, A/C) Status
2. Gathered points (from games and surveys)
3. Rank in the game
4. Frequency of visit to web portal
5. Weather metric such as humidity, temperature and solar radiation
6. Dummy features: Weekdays/Weekends/Midterms/Breaks/Finals

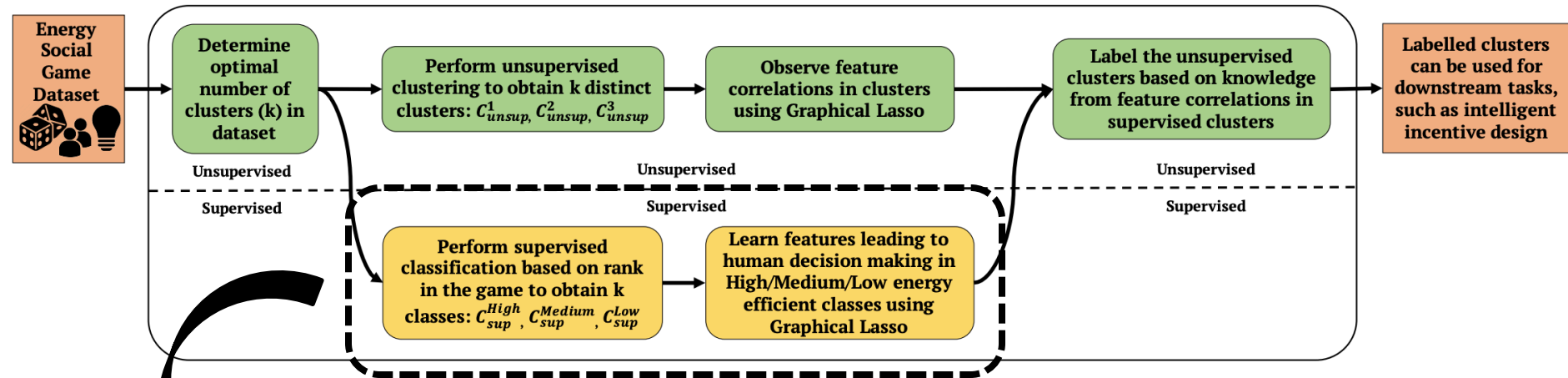
Ref: “Design, Benchmarking and Explainability Analysis of a Game-Theoretic Framework towards Energy Efficiency in Smart Infrastructure”, I. C. Konstantakopoulos, H. P. Das, A. R. Barkan, S. He, T. Veeravalli, H. Liu, A. B. Manasawala, Y. Lin and C. J. Spanos, *arXiv preprint arXiv:1910.07899*, 2019



Feature Correlation Learning using Graphical Lasso



Feature Correlation Learning using Graphical Lasso



For Medium energy efficient class

Temporal Dependencies

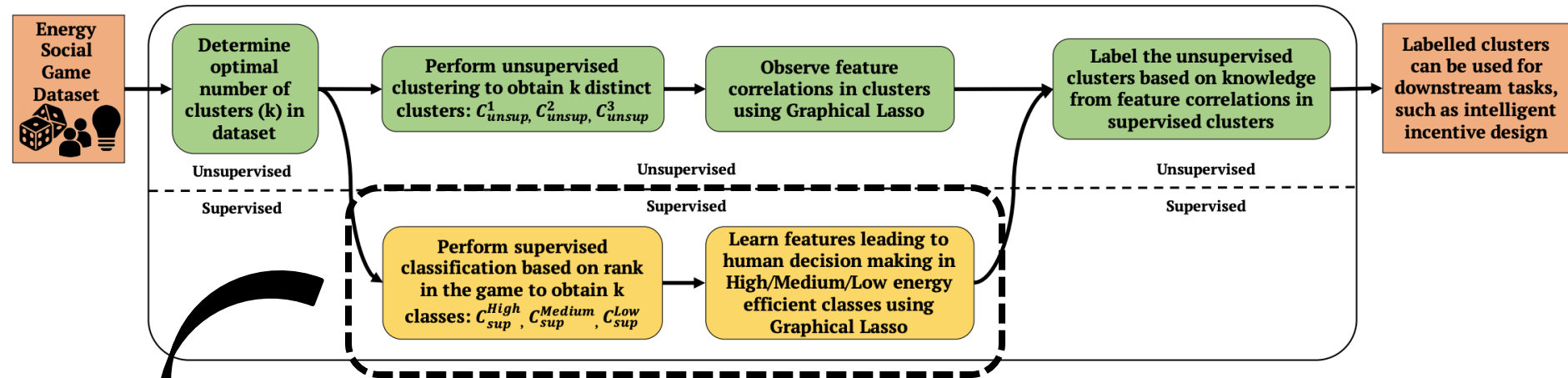
Ceiling Light Status	-	+	0	0	0	-	0	0	0	-	0	
Desk Light Status	-		0	0	0	0	0	0	0	0	0	
Fan Status	+	0	-	+	-	+	0	0	-	0	0	
Total Points	0	0	-		-	0	0	+	-	0	0	
Rank	0	0	+	-		0	0	0	-	-	0	
	Ceiling Light Status	Desk Light Status	Fan Status	Total Points	Rank	Morning	Afternoon	Evening	Break	Midterm	Final	Weekday

External Factor Dependencies

Ceiling Light Status	-	+	0	0	0	0	0	0	0	0
Desk Light Status	-	0	0	0	0	0	0	0	0	0
Fan Status	+	0	-	+	0	0	0	0	-	0
Total Points	0	0	-	0	-	0	0	0	0	0
Rank	0	0	+	-	0	0	0	0	0	0
	Ceiling Light Status	Desk Light Status	Fan Status	Total Points	Rank	Solar Radiation	Rain Rate	Temperature	Humidity	

Game Engagement Dependencies						
Ceiling Light Status		-	+	0	0	0
Desk Light Status	-		0	0	0	0
Fan Status	+	0		-	+	0
Total Points	0	0	-		-	-
Rank	0	0	+	-		+
	Ceiling Light Status	Desk Light Status	Fan Status	Total Points	Rank	Game Portal Visit Frequency

Feature Correlation Learning using Graphical Lasso



For High energy efficient class

Temporal Dependencies

	Ceiling Light Status	Desk Light Status	Fan Status	Total Points	Rank	Morning	Afternoon	Evening	Break	Midterm	Final	Weekday
Ceiling Light Status	-	+	0	0	0	0	0	0	0	0	0	0
Desk Light Status	-		0	0	0	0	0	0	0	0	0	0
Fan Status	+	0		0	0	0	0	0	0	0	0	0
Total Points	0	0	0		-	0	0	0	+	-	0	0
Rank	0	0	0	-		0	0	0	-	-	0	0

External Factor Dependencies

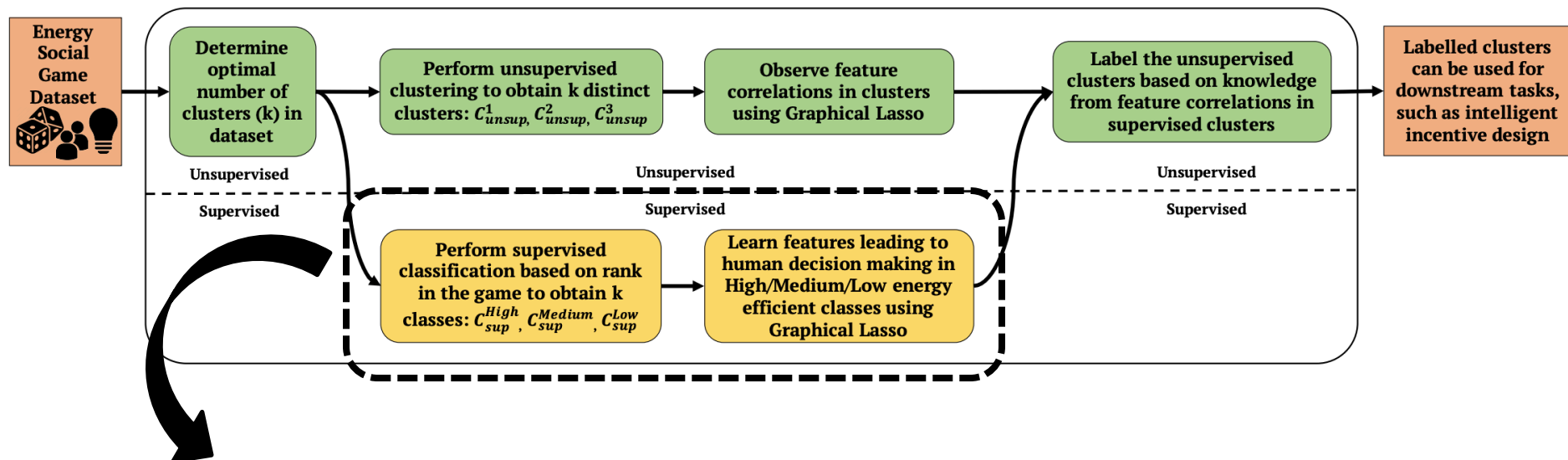
	Ceiling Light Status	Desk Light Status	Fan Status	Total Points	Rank	Solar Radiation	Rain Rate	Temperature	Humidity
Ceiling Light Status	-	+	0	0	0	0	0	0	0
Desk Light Status	-		0	0	0	0	0	0	0
Fan Status	+	0		0	0	0	0	0	0
Total Points	0	0	0		-	0	0	0	0
Rank	0	0	0	-		0	0	0	0

Game Engagement Dependencies

	Ceiling Light Status	Desk Light Status	Fan Status	Total Points	Rank	Game Portal Visit Frequency
Ceiling Light Status		-	+	0	0	0
Desk Light Status	-		0	0	0	0
Fan Status	+	0		0	0	0
Total Points	0	0	0		-	0
Rank	0	0	0	-		0

Causality Analysis using Grangers Causality

Enhances the explainability nature of our model

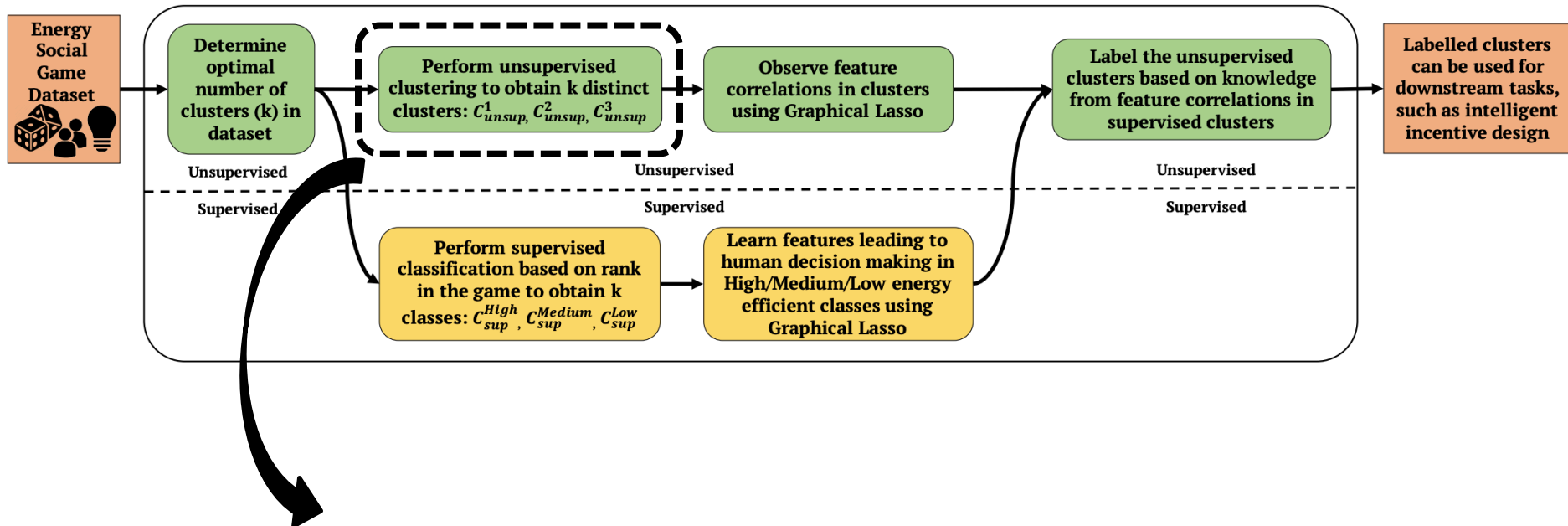


Test whether X causes Y	Fan \Rightarrow Ceiling Light		Humidity \Rightarrow Fan		Desk Light \Rightarrow Fan		Ceiling Light \Rightarrow Desk Light	
Player type	p-value	F-statistic	p-value	F-statistic	p-value	F-statistic	p-value	F-statistic
Low Energy Efficient	0.54	0.37	0.004	8.12	0.06	3.55	0.81	0.06
Medium Energy Efficient	0	21.2	0.008	7.06	0	113.6	0	25.8
High Energy Efficient	0	21.9	0.12	2.36	0.99	0.003	0.93	0.007

Under null-hypothesis, X does not cause Y

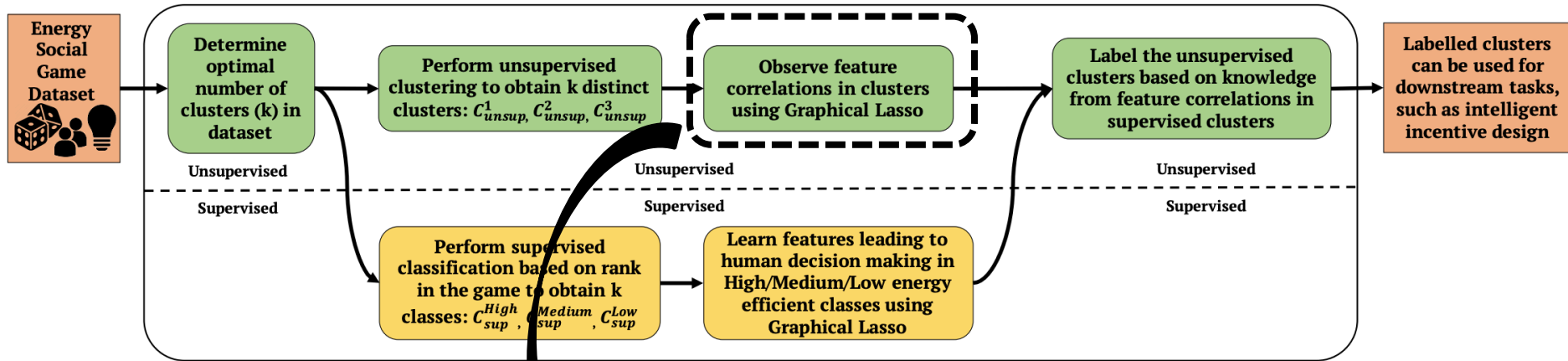
Afternoon \Rightarrow Fan		Evening \Rightarrow Ceiling Light	
p-value	F-statistic	p-value	F-statistic
0.01	6.1	0	25.3
0.46	0.55	0.0007	11.5
0.04	4.2	0.52	0.41

Unsupervised Clustering



Principal Component Analysis (PCA) followed by minibatch K-means

Feature Correlation Learning using Graphical Lasso



For an unsupervised cluster

Temporal Dependencies

	Ceiling Light Status	Desk Light Status	Fan Status	Morning	Afternoon	Evening	Break	Midterm	Final	Weekday
Ceiling Light Status		-	+	0	0	0	0	0	0	0
Desk Light Status	-		0	0	0	0	0	0	0	0
Fan Status	+	0		0	0	0	0	0	0	-

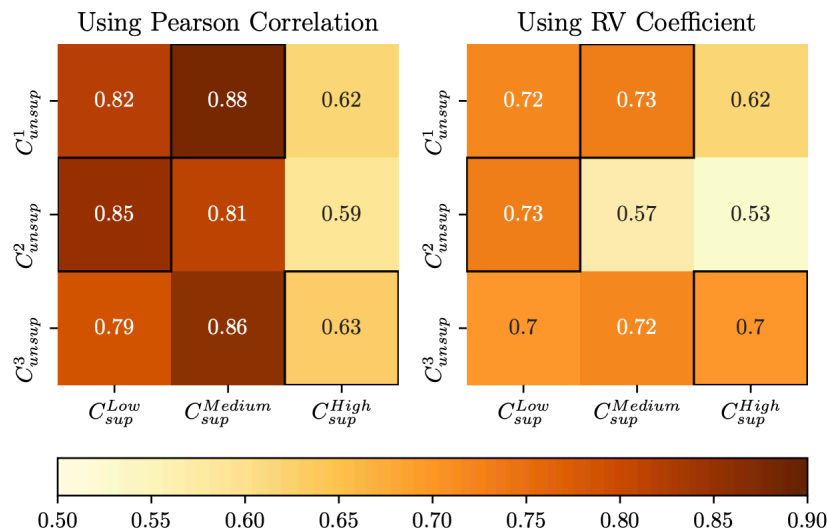
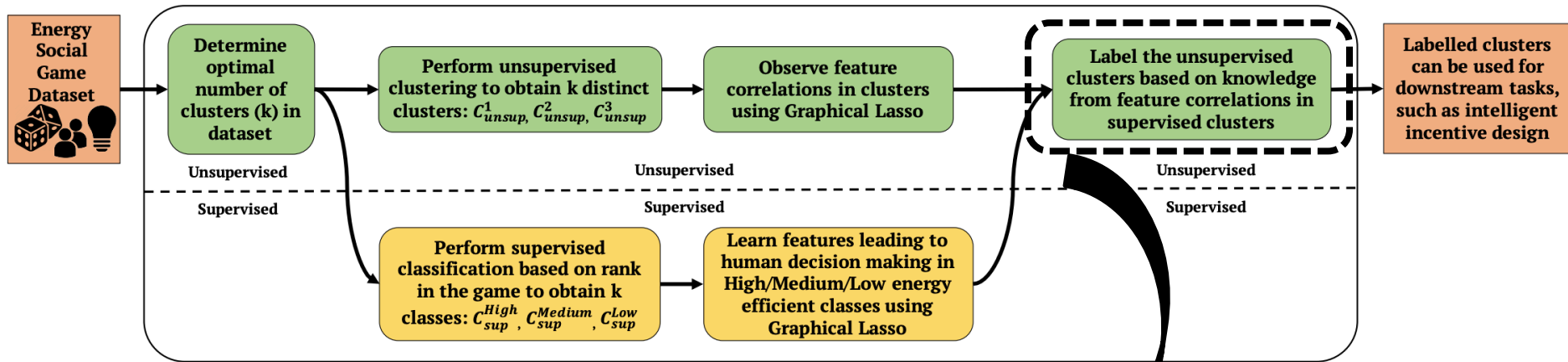
External Factor Dependencies

	Ceiling Light Status	Desk Light Status	Fan Status	Solar Radiation	Rain Rate	Temperature	Humidity
Ceiling Light Status		-	+	0	0	0	0
Desk Light Status	-		0	0	0	0	0
Fan Status	+	0		0	0	0	0

Game Engagement Dependencies

	Ceiling Light Status	Desk Light Status	Fan Status	Game Portal Visit Frequency
Ceiling Light Status		-	+	0
Desk Light Status	-		0	0
Fan Status	+	0		-

Feature Correlation Learning using Graphical Lasso

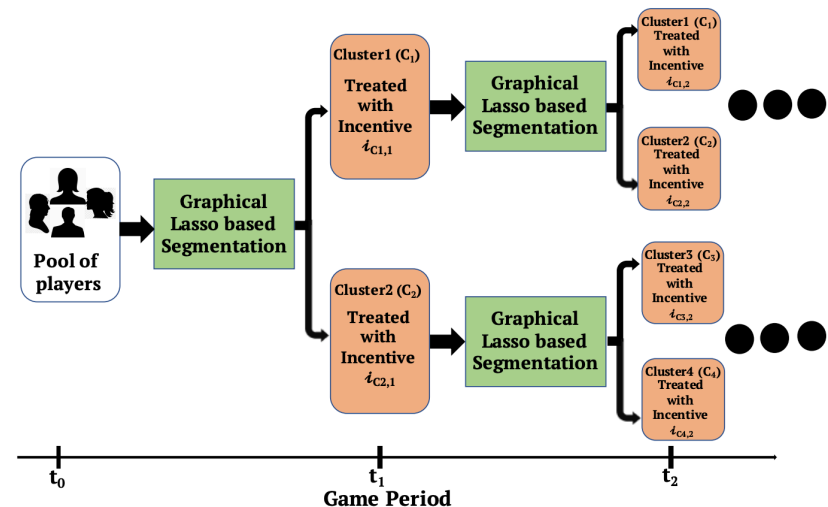


Conclusions and Future Work

- A framework for segmentation analysis in energy game-theoretic frameworks
- Clustering of agent behaviors and an explainable statistical model
- Characterization of causal relationship among several contributed features explaining decision-making patterns in agent's actions.
- Specific incentives can be designed for characteristic clusters

Future Work

- Tree based Incentive Design
- Study of long term effects of social game with improved incentive design



Thank You!

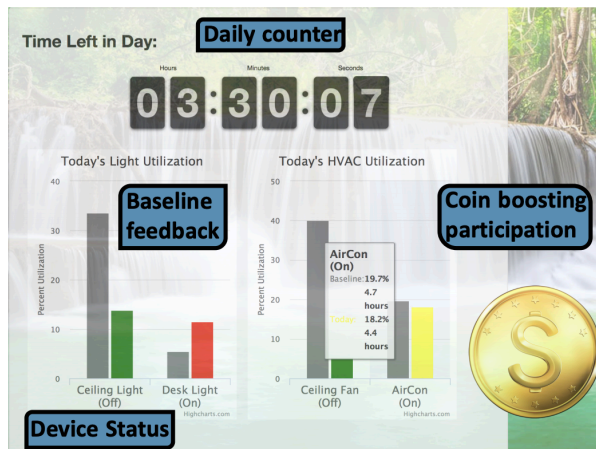
Questions?

References

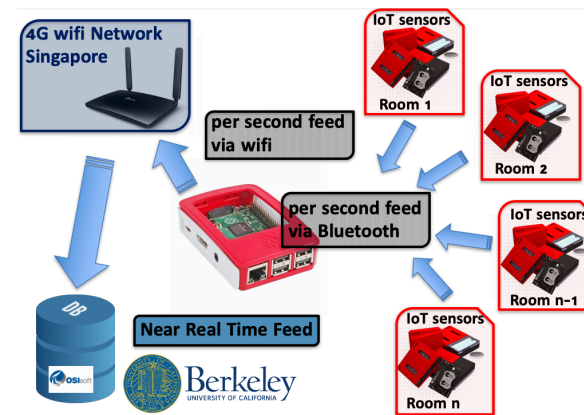
- “Design, Benchmarking and Explainability Analysis of a Game-Theoretic Framework towards Energy Efficiency in Smart Infrastructure”, Ioannis C. Konstantakopoulos, Hari Prasanna Das, Andrew R. Barkan, Shiying He, Tanya Veeravalli, Huihan Liu, Aummul Baneen Manasawala, Yu-Wen Lin and Costas J. Spanos, *arXiv preprint arXiv:1910.07899*, 2019
- “A Novel Graphical Lasso based approach towards Segmentation Analysis in Energy Game-Theoretic Frameworks”, Hari Prasanna Das, Ioannis C. Konstantakopoulos, Aummul Baneen Manasawala, Tanya Veeravalli, Huihan Liu and Costas J. Spanos, *arXiv preprint arXiv:1910.02217*, 2019
- Trevor Hastie, Robert Tibshirani, and Martin Wainwright. Statistical Learning with Sparsity: The Lasso and Generalizations. Chapman & Hall/CRC, 2015

Energy Social Game Experiment

- Experimental environment: Residential housing single room apartments in Nanyang Technological University (NTU), Singapore campus.
- Deployed IoT sensors for energy resource observation and employed an web-interface for interaction with players
- Energy usage observed: Ceiling Light, Desk Light, A/C and Fan
- Occupants were rewarded with points based on how energy efficient their daily usage is in comparison to their past usage and usage of other players in the game.



(a) Graphical user interface (GUI)



(b) Social game dataflow architecture design